Medical Knowledge Discovery Systems: Data Abstraction And Performance Measurement

By: Albert L Harris, **Charlie C. Chen**, William J Perkins

Abstract

Knowledge discovery systems can be traced back to their origin, artificial intelligence and expert systems, but use the modern technique of data mining for the knowledge discovery process. To that end, the technical community views data mining as one step in the knowledge discovery process, while the non-technical community seems to view it as encompassing all of the steps to knowledge discovery. In this exploratory study, we look at medical knowledge discovery systems (MKDSs) by first looking at three examples of expert systems to generate medical knowledge. We then expand on the use of data abstraction as a pre-processing step in the comprehensive task of medical knowledge discovery. Next, we look at how performance of a medical knowledge discovery system is measured. Finally, the conclusions point to a bright future for MKDSs, but an area that needs extensive development to reach its full potential.

Albert L Harris, **Charlie C. Chen**, William J Perkins (2004) "Medical knowledge discovery systems: data abstraction and performance measurement" *Knowledge Management Research & Practice* #2 pp.95–102 Version of Record Available @ www.sciencedirect.com [DOI:10.1057/palgrave.kmrp.8500027]

Introduction

Medical errors resulted in 98,000 patient deaths (Institute of Medicine, 1999), 2.4 million extra days of hospitalization, and $9.3 billion in excess charges according to the Agency for Healthcare Research and Quality (McGee, 2003). Much of the mortality and mishaps can be attributed to the medical diagnosis errors that are caused by problems with charting procedures, erroneous and inappropriate documentation, insufficient knowledge in a medical domain, inappropriate tests, and a myriad of other reasons. By using medical software applications, medical errors can be reduced, while the integrity and reliability of the diagnosis process can be improved. In addition, caregiver departments could reduce diagnosis costs by using the applications. Also, turnaround times for medical diagnosis could be decreased as caregivers would be able to quickly reach high-quality diagnosis decision in minutes. Finally, administration and support costs for hospitals and clinics could be reduced.

Along with the adoption of medical software applications, there has been a prodigious increase in the amount of data gathered, stored, and shared in hospitals and healthcare institutions. The collection of data itself, however, has not and will not be useful to anyone without effective tools to support the analytical and evaluative use of the data. The field of healthcare informatics aims to help close the gap between data gathering and data exploitation, for the purposes of enhancing the provision of health care.

Intelligent data analysis (IDA) is an interdisciplinary field of study that directly addresses the above needs by utilizing machine learning, pattern recognition, data abstraction, visualization, and statistics (Lavrač *et al.*, 2000). Information systems with the IDA capability may include knowledge-based systems, decision support systems, intelligent agents, and knowledge management systems. These systems are intelligent because they can explain and justify their behaviors and decision (Gregor & Benbasat, 1999).

Knowledge discovery in databases (KDD) is a process used to exploit knowledge found in the data by performing the following steps: proper selection of data by understanding the domain, data cleaning and preprocessing, data mining, and interpretation and evaluation (Lavrač, 1998; 1999). For instance, the new data of molecular biology can be combined with clinical medical data to 'achieve a higher-resolution understanding of the casues for and treatment of disease' (Han *et al.*, 2002, p 54).

There are many problems associated with typical data sets in medicine that suppress knowledge discovery. Among these are incompleteness (data are missing parameter values), incorrectness (inaccurate or noisy data), sparseness (few patient records that pertain to the problem), and inexactness (Lavrač *et al.*, 2000). Data abstraction aims to overcome these hindrances to knowledge discovery by handling noise and missing data, and by mechanisms for dealing with temporal data. Therefore, the process of data abstraction is critical to the success of any medical knowledge discovery systems (MKDS).

Once the data are ready, appropriate machine learning methods, which are frequently thought of as data mining, are applied. Machine learning methods have several approaches to aid in diagnosis, prognosis, and patient management. They can construct a set of rules that generalize training cases, they can store the training cases for reference to help classify new cases, and they can compute the conditional probability of each class using the Bayesian formula. The role of MKDS is to use these rules and act as an intelligent assistant to the physician or medical specialist by allowing them to perform their jobs more effectively. The incisive evaluation and interpretation of the findings of MKDS is crucial in eliminating any incredulous views that physicians may make in the purchase or use of MKDS. It is important to note that the main goal of MKDS is to aid the physician, not to replace physicians.

Origins of MKDSs

MKDSs can be traced to artificial intelligent (AI) systems. AI's focus in the 1970s and early 1980s was on the development of systems used to support diagnosis and decision-making. These systems were called expert systems or decision support systems. Problems addressed at the early stage were knowledge acquisition and knowledge representation, which dealt with explaining the reasoning and the user interface associated with the expert system. In the first generation of expert systems, experts themselves put knowledge into the system. Problems soon surfaced with this technique because of human-defined rules and human-defined knowledge. This approach did not deal with the biases associated with the expert. It also held rules in a largely flat organization, which corresponded to a lack of hierarchical understanding (a comprehensive view) of these rules.

In the late 1980s and early 1990s, knowledge was acquired by the analysis of data and example cases stored in databases. The decision support system (DSS) was developed to analyze data via decision rules and models. As the decision process becomes more complex for certain problem domains, such as medical clinics, the predetermined rules and models may not be sufficient. Instead, experts' inference skills based on their knowledge and experiences become more important. As such, the expert system (ES) was created to have reasoning mechanisms to explain and justify decisions. Although DSS and ES serve different purposes, there are synergetic results when integrating these two systems. Because of its unbiased decision-making process, ES can complement with the biased nature of DSS to acquire and evaluate information based on the predetermined rules (Turban, 1986). Hence, it is often seen that an ES used with a DSS has a capability to provide both 'what if' and 'why' decisions. The DSS now had the expert not as the sole source of knowledge, but as the person interacting with the process to construct the knowledge base (Lavrač *et al.*, 2000) by supplementing the knowledge gained by the system. The expert also provided background knowledge to support the learning of rules by focusing and guiding the process.

As these systems evolved, it was discovered that general problem-solving techniques were insufficient. What was needed was specific knowledge (deep causal knowledge) about the application domain, rather than broad, general knowledge (shallow level knowledge). Another area of inadequacy related to general problem-solving techniques is that they cannot dynamically change the meaning of measurements based on the context of the situation (i.e. different patients/conditions may constitute different values that are considered to be abnormalities). Also, the first-generation systems were incapable of dealing with the large databases and data warehouses that were becoming omnipresent in the industry (Cabena *et al.*, 1998). Fried *et al.*, (2002) have outlined the limitations associated with the use of general problem-solving techniques that do not employ the use of knowledge.

In the domain of medical clinics, these systems have difficulty in the fast and correct detection of slow trends in patient states. The reason for this is that, especially in patient monitoring systems, the system is designed to detect large changes (with high a probability of certainty) to accommodate life-threatening complications. As a result, the system misses the small, subtle changes in a patient's state. Secondly, these systems only detected the trends; they could not quantify them in terms of how they relate to medical knowledge. It became clear that the integration of knowledge into these problem-solving systems was needed. We began to see the development of systems that either used knowledge about the problem domain or knowledge about the underlying principles of the data analysis process itself. These systems were said to be 'intelligent' in the sense used in AI (Lavrač *et al*., 2000).

AI is the field of study that uses computational techniques for performing tasks that require intelligence when performed by humans. Computers excel in functions such as computations and data storage. These functions are algorithmic and repetitive in nature, in the sense that basically they just involve transforming inputs or repeating a process to create outputs. Humans, however, are better at solving problems, which use symbols rather than numbers, like scheduling events or understanding a poem. MKDS embedded with AI functions can automate algorithmic and repetitive tasks, and improve diagnosis accuracy.

This paper proposes that MKDS is the area of information technology that supports the analysis of medical data and the discovery of medical knowledge that is encoded, or hidden, in the medical data. Medical knowledge discovery in databases is the process of extracting medical knowledge from (typically large) databases by performing the steps outlined later in this paper. Given the emerging field of MKDS, many questions regarding the use of MKDS, its benefits and weaknesses, as well as justification of its usage remained unanswered. Without a clear set of questions to address in the study, the exploratory study is a more appropriate research method. The final product of this paper can provide more lucid insights on the existing status of MKDS and its future development.

Alternative views on medical knowledge discovery processes

There is currently a fundamental difference in how the understanding of the overall process and the terminologies involved in medical knowledge discovery processes are viewed. It seems that a continuum has formed, with the non-technical, business communities on one end, and the scientific, mathematical communities on the other end. The non-technical communities typically view data mining as a term that encompasses the steps of (1) selecting the data that will be used, (2) deciding granularity, (3) establishing techniques for pre-processing data and (4) interpreting the results. This group, gathered on one end of the continuum, views data mining as a comprehensive term that encompasses all the steps necessary achieve knowledge discovery.

On the other end of the continuum, there are the scientific and mathematical communities. They tend to view data mining as but one step in the overall process of KDD. In their view, KDD is made up of the following steps: (1) understanding the domain, (2) selecting and pre-processing data, (3) extracting knowledge (data mining), and (4) interpreting and evaluating the results.

We propose that the steps that are taken to achieve the final result, acquiring knowledge, are basically the same. It is just a matter of difference in terminology and structure of the processes. For example, data abstraction has also been called data transformation. One other difference that perhaps has less to do with terminology is the role of experts. Cabena *et al*., (1998) define data mining as 'the use of methods that can automatically extract information from data with little or no user interventiony' (p xi). Alternatively, Morik *et al*., (2000) assert that the expert must play a crucial role in the knowledge discovery process, and in the knowledge-based system. They think it is impractical to presuppose that the role of the expert could be eliminated, especially in medical parameters. This paper more closely follows the scientific communities' view of the overall understanding and terminologies associated with the research done on intelligent data analysis.

MKDS

This paper selectively identifies and discusses three different approaches to MKDS to illustrate their medical applications.

MYCIN

MYCIN was developed in the 1970 s at Stanford University (Buchanan & Shortliffe, 1984). This system aids in the process of diagnosis by determining the infectious agent in a patient's blood. It also aids in prognosis by recommending a specific treatment for the infection that was found.

MYCIN represents knowledge by a set of IF–THEN rules. The following is an example of the pseudocode that made up one of MYCIN's rules (Heriot-Watt University, 1994).

IF the infection is primary-bacteremia
  AND the culture's site is one of the sterile sites
  AND the hypothesized portal of entry is the gastro-intestinal tract
    THEN there is suggestive evidence (0.7) that the infection is bacteroid.

The 0.7 in the consequence of the rule above is the certainty factor, or the certainty that the conclusion will be true.

This is primarily a goal-directed system. It uses a backward chaining reasoning approach. MYCIN is also heuristically guided. By asking questions in the right order, the system avoids asking questions that could easily be eliminated. For example, if we know a patient's age to be 10 years, it would be inappropriate to inquire about alcohol abuse.

One heuristic strategy employed by MYCIN was to first ask general, required, pre-set questions that allow the system to define the problem space. It then rules out unlikely diagnoses and unnecessary searches. After this, it moves to more specific questions to try to prove possible

Table 1 Comparison of three MKDSs.

	MYCIN	*RÉSUMÉ*	*VIE-VENT*
Year Built	1970s	1993	1996
Purpose of system	Aids in the process of diagnosis by determining the infectious agent in a patient's blood	Framework for interpreting data in a time-ordered clinical domain	Monitoring and therapy planning for artificially ventilated infants
Domain(s)	Single	Multiple	Single
Knowledge representation	IF–THEN rules	Knowledge-based temporal-abstraction	Measurement and comparison

blood infections. To develop rules, MYCIN first checks all the antecedents of the rule to see if any are known to be false. Another heuristic strategy used in this system deals with the certainty factor. It looks at the rule with the more certain conclusions first, and then abandons the search if the certainty factor gets below 0.2 (Heriot-Watt University, 1994).

RÉSUMÉ

RÉ SUMÉ is a system for generating temporal data abstractions and was developed by Shahar & Musen (1996). The developers defined a knowledge-base framework for interpreting data in a time-ordered clinical domain. Their problem-solving method is called the knowledge-based temporal-abstraction (KBTA) method developed by the Stanford School of Medicine. RÉSUMÉ was built and tested for a number of clinical domains; perhaps the one it is most popular for is patients with insulin-dependent diabetes. In general, RÉSUMÉ was not created for any one particular domain, but was intended to be used among several domains.

One feature of RÉSUMÉ that is significant is that the abstractions are generated on the basis of interpretation contexts, so the type of information is said to be context sensitive. Several interpretation contexts can be done at the same time and therefore we could have different interpretations for the same data. Despite the exemplary features associated with RÉSUMÉ, Miksch *et al*., (1996) could not use it in their domain of therapy planning for artificially ventilated infants. Two major reasons are the system's limited domain dynamics, and inability to perform the temporal interpolation subtask and to handle low-frequency observations.

VIE-VENT

VIE-VENT was developed by Miksch *et al*. around 1996 for a specific application domain. Unlike RÉSUMÉ, VIE-VENT does not try to formulate generic knowledge. The intended domain is monitoring and therapy planning for artificially ventilated infants. The researchers propose that the two most critical aspects of intelligent data analysis are data validation and therapy planning. Data validation is the process of obtaining reliable measurements, and therapy planning is decomposed into three tasks – selecting, predicting and adopting (Miller, 1956).

The output of VIE-VENT consists mainly of therapeutic recommendations for changing the settings on the machine that is used to ventilate the newborn. It can also aid in monitoring the patient, by giving warnings in critical situations and giving comments and explanations about the state of the newborn's respiratory system. The frequency of output data depends on the infant's state and the requirements of the therapy planning strategy. In VIE-VENT, the meanings of the recordings (context intervals) are not dynamically derived, but are defined in the system and can be tailored to a particular patient as appropriate.

Table 1 provides a comparison of the three different approaches to MKDSs.

Medical knowledge discovery processes

Medical KDD is a process that is primarily concerned with fostering the practical analysis of medical data, and gaining acumen at the hidden relationships and patterns in the medical data. This is usually achieved by performing the following four steps (Kudoh *et al*., 2003):

Step 1. Understanding the Medical Domain: The MKDSs solve medical problems by first generating a set of rules, then applying those rules to new medical cases through the use of deduction, which involves linking rules together and making associations, also known as abduction. This process begins with understanding the medical domain in question.

Step 2. Searching the Problem Space: Once the domain is understood, the next step is to prepare the data so that processing can be performed. Medical data sets are often characterized by their incompleteness, incorrectness, and unavailability of appropriate data (Lavrač, 1999). Machine learning tools, especially those concerned with data abstraction, were developed because they had to deal with these imperfect characteristics of medical data sets. In the overall medical knowledge discovery process, it is important to form the data set and cleanse the data. The knowledge base is the heart of an ES, and it needs to be as complete and consistent as possible (Lavrač *et al*., 2000). For this reason, the domain experts (physicians) should be extremely interactive with the process of evaluating the results. Medical knowledge discovery processes frequently extract meaningless relationships and useless knowledge, which is why evaluation and interpretation are so important.

Step 3. Data Analysis Methods: Lavrač *et al.*, (2000) propose two main categories of intelligent data analysis methods: data abstraction and data mining. *Data abstraction* is concerned with supporting specific knowledge-based activities through the intelligent interpretation of patient data. *Data mining* is concerned with discovering new medical knowledge through the knowledge-driven analysis of representative collections of example cases (Feelders *et al.*, 2000).

Step 3.1. Medical Data Abstraction: Data abstraction is a process that supports the acquisition of the *specific knowledge* required by an intelligent system. The specific knowledge in medical problem solving relates to the tasks of diagnosis, prognosis, patient monitoring, patient management, etc., through the intelligent analysis of the raw patient data stored in the database (Lavrač *et al.*, 2000). The goal of data abstraction is to describe data in a better way, relative to the problem, so that the specific knowledge can be generated, which enables a 'path' to be discovered.

In medicine, knowledge is expressed in panoramic terms, as in associations of rules, treatment protocols, models of different pathophysiological statuses, guidelines, etc. (Lavrač *et al.*, 2000). This is very different from data gathered from a particular patient, which is made up of various numeric measurements (blood pressure, body temperature, heart rate, prostate-specific antigen measurements, etc.). A particular patient's information consists of the history of the patient (i.e. past surgery), pharmaceutical records, laboratory examinations, symptoms, etc. Notice that there is a fundamental difference in the level of granularity between medical knowledge and patient data. This is a great hindrance because patient data must be matched and compared to the medical knowledge so that problem solving can be accomplished (Lavrač *et al.*, 2000).

To begin the process of problem solving, patient data and medical knowledge must be expressed at the same level of granularity so that they can be compared. This is often difficult because the raw patient data are usually highly specific and medical knowledge is highly abstract. Data abstraction is the process of transforming the patient data so that they are on the same level of granularity or abstraction as the medical knowledge. Therefore, data abstraction can be viewed as a critical pre-process to extracting medical knowledge (the data mining process).

Raw patient data can be very noisy (contain unexpected or erroneous information) or contain outliers in some domains. An example of an outlier is having 110 years for a person's age. Noisy data can cause outliers in the analysis. Hence, it should either be corrected or dropped from the data set. The presence of erroneous data in a clinical information system can be attributed to the fact that most variables are entered into the system by hand. Specifically, only 5–10% of all variables are entered into a clinical information system automatically (Morik *et al.*, 2000). The automation of the data entry process is a primary area for medical research. While automation of the data entry process for medical data is improving, it is highly unlikely that most of the medical data entry will be automated in the near future. Noise is unavoidable, so data abstraction as a critical pre-process has been stressed.

Most data abstractions in medical parameters are concerned with the interpretation and pre-processing of temporal data, because time is intrinsic to most medical problem domains. Pathophysiological is temporal, that is it evolves over time. Patient information itself involves the history of the patient, treatment of diseases, and patient monitoring. The collection of a patient's history is impossible without considering the element of time. Time is an explicit dimension to patient data; therefore, it plays a key role in data abstraction and medical knowledge. Temporal data abstraction may include (1) merge abstraction, (2) persistence abstraction, (3) trend abstraction, and (4) periodic abstraction (Lavrač *et al.*, 2000). When the data abstraction process is applied to real patient data, quantitative values need to be transformed into qualitative values to aid in the data validation component. Data validation is important because the amount of errors in the actual patient data has proven to be astonishing in some domains. After the data set has been formed, it is appropriate to move to the overall MKD process: extracting the regularities hidden in the medical data.

An MKDS designed to aid in problem solving, and provide support for medical activities (such as diagnosis, prognosis, monitoring, and the discovery of unprecedented information) must be able to perform a data abstraction process.

Step 3.2. Mining Medical Data: Data mining can be a powerful tool to supplement and perform many tasks in the medical domain (Shahar & Musen, 1996). Suppose an oncologist wants to analyze the relatedness of the size, shape, and color of a particular gastrointestinal tumor to determine if the patient has symptomatic metastatic carcinoid disease. The patients would be organized in tables based on the category of tumor they have (whether neuroendocrine or decarboxylation). The rows in the tables would be actual patients having a particular tumor, and from whom data have been gathered. The columns in the table could be tumor size, tumor shape, tumor color, and any other attribute of the patient's tumor that is of interest. Patients who have already been diagnosed with this disease are examples of training examples that have already been classified. Using training examples that have already been classified to determine unknown cases is called *supervised learning*. Using training examples that have yet to be classified is called *unsupervised learning*. Thus, the patients who have yet to be diagnosed are considered unclassified training examples, and any learning done with these instances is considered to be unsupervised (Cabena *et al.*, 1998).

Of all of the reasoning approaches used in MKDS, there are three useful approaches: (1) rule-based reasoning, (2) case-based reasoning, and (3) statistical and pattern recognition. Rule-based reasoning approach encompasses at least one of four reasoning rules. The first is to construct the rules in the IF–THEN format, such as 'IF condition(s) THEN conclusion.' The second is the rule induction by constructing a sequence of events that directs a set of data toward a conclusion, solution, or answer. The third is to build up an associative relationship between two variables. For instance, if a person is found to be wet, then using abduction we conclude that snorkeling could be a possible explanation for the wetness. Decision tree analysis is another reasoning rule. However, decision tree analysis is less useful and accepted in the medical community, because of the minimal amounts of nodes.

Case-based reasoning approach differs from rule-based reasoning in using the explicit knowledge gained from documented, past situations to gain insight on new cases. Case-based reasoning often uses a hierarchical database structure (Lavrač *et al.*, 2000). A hierarchical database is a collection of records that is organized (logically) in a 'tree' manner (Pratt & Adamski, 1991). The hierarchical database is great for maintaining data integrity and for data independence. When using this technique, there are several issues that must be addressed and investigated. One issue to address is how appropriate are the proposed solutions? What works for one patient cannot be assumed to work for another patient; they may have different allergies, ages, and physical conditions. Secondly, one must consider the reality of the historical cases. Medical knowledge is changing every day. Treatment protocols become outdated as new regimens take their place. For example, electro-shock therapy was once used extensively for psychiatric patients, but it is rarely used now. Another major area of complication is that different doctors prefer and use different solutions. Therefore, the most frequent solution in rule-based reasoning for a given problem could be due to homogeneity of the type of doctors and their treatment actions in the old cases.

The third reasoning approach is the statistical and pattern recognition method. This method is sub-symbolic in nature. This means that statistical and pattern recognition reasoning does not produce knowledge in the form of human understandable symbols, and humans have a hard time understanding how statistical and pattern recognition reasoning comes up with the conclusions that have been drawn. Nevertheless, statistical and pattern recognition reasoning is effective and oftentimes more accurate than domain experts in the task of classification. The Bayesian classification method is widely established and used in medical classification, compared to the instance-based learning. The Bayesian classification method used Bayes' theorem (a well-known mathematical formula that classifies the probability of an event given a prior event) to classify cases by calculating the probability of each class. Bayes' theorem can also be used to estimate the conditional independence of the attributes of a given instance that is to be classified.

There are some problems associated with using the Bayesian classifier as part of an expert MKDS. Perhaps the biggest disadvantage to using the formula is the amount of probability data needed, which is sometimes more than what is actually available. This is especially true with regard to medical data. If the conclusions are not mutually exclusive and the attributes are not conditionally independent, then the amount of probability data that is needed further increases. Another problem with using Bayes' theorem is that some calculations can be brought to a standstill if missing only one of the pieces of probability data (Barzilay *et al.*, 1998). The probability data themselves must be valid and unbiased. Further, the sample sizes from which these data have been gathered must be sufficient, to adequately represent the population in question. This is often a difficult task.

It is also necessary to mention the difficulty of getting physicians to accept the decisions derived by the formula when these results are conveyed in a numerical, sub-symbolic way. The results that are derived are displayed numerically, in a way that does not explain *how* these conclusions are reached. When associations are reduced to numbers, it reduces the ability to understand the reasoning behind the associations, which confuses users. Therefore, physicians in general distrust systems that do not provide transparent explanations that describe how a particular conclusion was reached (Barzilay *et al.*, 1998). Bayesian approaches that reduce discovered knowledge to numbers makes using the knowledge with other tasks very difficult. This reduces the likelihood of creating a generic knowledge base that can be used in multiple situations, which is one goal of data mining.

Step 4. Interpretation and Evaluation of Results: An expert system must be able to explain and justify the decisions it reaches. How well physicians can interpret the decision-making process is crucial when determining whether the decision the expert system has reached will stand. Interpretability comes into even more scrutiny when the system reaches an unexpected result.

Measuring success of MKDS

Most hospitals' current considerable medical errors and associated cost can be greatly reduced with the successful adoption of MKDS. This can result in a more precise diagnosis process to fast and accurately diagnose patient's symptoms. Administration and support cost for hospitals and clinics can also be reduced. More importantly, MKDS can supplement the scarcity of physicians in some specialized domains in some remote areas. To realize these benefits, it is important to have stakeholders of MKDS to adopt the information system.

Information systems adoption is one of key dependent variables to determine the success of a new information system in MIS research (DeLone & McLean, 1992). Different factors are identified to determine the adoption of different information systems (Davis, 1989; Moore & Benbasat, 1991). The determinants for the success of MKDS also can be the acceptance and usage of the system by their users. Acceptance generally depends on two factors: the system's performance and the interpretability of the results of the system. The prospective presence of AI in medicine will depend on these two things. This section will cover how performance is measured and will discuss how the results are explained.

Performance evaluation

Evaluating the performance of an MKDS depends on the task assigned to the system. For the tasks of diagnosis and prognosis, *classification accuracy* is often the most frequently used measurement of performance, although it is not always the best measurement. Classification accuracy is used to develop rules in the rule induction process, but it can also be used to evaluate the entire classifier.

Information score

The information score is another, perhaps better, way to evaluate the performance of a classifier (Lavrač, 1998; 1999). The most general way a system can convey results is by a probability distribution over the events in the sample space. The information score is a reliable way to measure performance because it takes into account the prior probabilities of the individual events within the sample space. In domains where one of the classes is highly likely, it is easy to achieve accuracy. For example, a given system almost always correctly diagnoses (classifies) painful joints in patients over 70 years of age as rheumatoid arthritis. Is the reason that the classifier is almost always correct due to the 'insight' of the system, or the fact that 2.1 million adults in the US have rheumatoid arthritis? The amount of information that the system (classifier) actually provided to aid in the correct diagnosis could in fact be very low.

The information score can be computed as follows:

The prior probability of the class is greater (þ) or less (-) than the probability returned by the classifier depends on domains:

*I*ðekÞ ¼ - logðPciÞ þ ð - ÞlogðPcjÞ

where *I*(ek) is the the amount of information gained by the classifier; Pci the prior probability of the class and Pcj the probability returned by the classifier

Sensitivity and specificity as measures of performance

In medical domains, *sensitivity* and *specificity* are more commonly used to evaluate performance than classification accuracy. In some situations, these measurements are more important than accuracy. Sensitivity can be viewed as a detection rate (as in the detection rate of a certain disease) that should be maximized. It is computed by calculating the percent of positive cases that are actually classified as positive. It can be represented mathematically by the formula:

$$Sensitivity = \frac{TP}{TP + FN}$$

where TP is the true positives, a correct classification of a positive case and FN the false negatives, an incorrect classification where a case that was actually positive was put into a negative class.

It is worth noting that to achieve the goal of increasing sensitivity, the number of correct classifications of positive cases (TP) should be increased and the number of false negatives (FN) should be decreased. This increases the numerator while decreasing the denominator, which mathematically increases the percentage.

Conclusions

With the recent development in technologies for data gathering, data storage, and data communication and networking, data are more accessible than ever. What has not evolved so efficiently perhaps, are the tools needed to interpret the information effectively in the data.

There will be numerous future developments that will make MKDS more prevalent in medical procedures. One unarguable area of development that will influence the future proliferation of MKDS is the promulgation of standards. Standards are needed in terminology, especially since the MKDS field is very much a global, multilingual effort. Standards are also needed for the understanding of the overall process of MKDS and all it entails. This is especially true when describing data mining as just one step in the overall medical knowledge discovery process. The reusability of data and knowledge will also greatly impact the development of new medical knowledge through the creation of generic machine learners that can be used in multiple domains.

Another area of further development is textual mining, which describes the process of extracting information from medical texts and document images. A medical knowledge discovery approach has proven to be very effective in this area (Weeber & Vos, 1998). To augment this field of study, methods have been developed to handle errors in textual data such as misspelled words (Ruch *et al*., 2002).

Although not much research has been reported at this time, the communication among learners is another area of importance. What this means is that one machine learner produces a conclusion, which is then used as input to other learners in the form of background knowledge. This has been researched in the area of 'meta' learning, boosting, and bagging. We propose that communication among learners could be supported by standards in communication protocols and languages, much like the way PERL and XML are used.

Machine learners themselves also have requirements if they are to be prevalent in the future of medical settings. Clark & Niblett (1989) have identified three requirements: accurate classification, simple rules, and efficient rule generation. Also, effective data validation is a necessary area of future development, especially with data collected from patient monitoring systems (Horn *et al*., 1997).

MKDS will provide enhanced medical treatment and patient management, along with more efficient budget utilization. MKDS have been proven to help doctors make better decisions. They can also save time and money by eliminating unnecessary tests and genuinely empowering physicians and medical experts.

References

BARZILAY R, MCCULLOUGH D, RAMBOW O, DECRISTOFARO J, KORELSKY T and LAVOIE B (1998) A new approach to expert system explanations. In *Proceedings of the Ninth International Workshop on Natural Language Generation* pp 78–87, Niagara-on-the-Lake, Canada.

BUCHANAN BG and SHORTLIFFE EH (Eds) (1984) *Rule Based Expert Systems: The Mycin Experiments of the Stanford Heuristic Programming Project*. Pearson Addison Wesley, Reading, MA.

CABENA P, HADJINIAN P, STADLER R, VERHEES J and ZANASI A (1998) *Discovering Data Mining: From Concept to Implementation*. Prentice Hall, Upper Saddle River, NJ.

CLARK P and NIBLETT T (1989) The CN2 Induction Algorithm. *Machine Learning Journal* 3(4), 261–283. http://www.cs.utexas.edu/users/pclark/papers/cn2.ps (Retrieved 17 November 2003).

DAVIS FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13(3), 319–340.

DELONE WH and MCLEAN E (1992) Information system success: the quest for the dependent variable. *Information Systems Research* 3(1), 60–95.

FEELDERS A, DANIELS H and HOLSHEIMER M (2000) Methodical and practical aspects of data mining. *Information and Management* 37(5), 271–281.

FRIED R, GATHER U and IMHOFF M (2002) *Pattern Recognition in Intensive Care Online Monitoring*. citeseer.nj.nec.com/450368.html (Retrieved November 14, 2003).

GREGOR S and BENBASAT I (1999) Explanations from intelligent systems: theoretical foundations and implications for practice. *MIS Quarterly* 23(4), 497–530.

HAN J, ALTMAN RB, KUMAR V, MANNILA H and PREGIBON D (2002) Emerging Scientific Applications in Data Mining. *Communications of the ACM* 45(8), 54.

HERIOT-WATT UNIVERSITY (1994) *MYCIN: A Quick Case Study*. http://www.cee.hw.ac.uk/Balison/ai3notes/section2_5_5.html (Retrieved 11 November 2003).

HORN W, MIKSCH S, EGGHART G, POPOW C and PAKY F (1997) Effective data validation of high-frequency data: time-point-, time-interval-, and trend-based methods. *Computers in Biology and Medicine* 27(5), 389–409.

INSTITUTE OF MEDICINE (1999) *To Err is Human: Building a Safer Health System*. National Academy Press, (Washington, DC).

KUDOH Y, HARAGUCHI M and OKUBO Y (2003) Data abstractions for decision tree induction. *Theoretical Computer Science* 292(2), 387–416. http://dx.doi.org/10.1016/S0304-3975(02)00178-0 (Retrieved 14 November 2003).

LAVRAČ N (1998) *Data Mining in Medicine: Selected Techniques and Applications*. citeseer.nj.nec.com/lavrac98data.html (Retrieved 14 November 2003).

LAVRAČ N (1999) Selected techniques for data mining in medicine. *Artificial Intelligence in Medicine* 16(1), 3–23.

LAVRAČ N, KERAVNOU E and ZUPAN B (2000) *Intelligent Data Analysis in Medicine*. citeseer.nj.nec.com/article/lavrac00intelligent.html (Retrieved 18 November 2003).

MCGEE MK (2003) Putting a clamp on medical mishaps: data warehouses and picture-archiving systems can reduce patient risks. *Information week* 13 October 2003, p 30.

MIKSCH S, HORN W, POPOW C and PAKY F (1996) Utilizing temporal data abstraction for data validation and therapy Planning for artificially ventilated newborn infants. *Artificial Intelligence in Medicine* 8(6), 543–576.

MILLER G (1956) The marginal number seven, plus or minus two: some limits to our capacity for processing information. *Psychological Review* 63(2), 81–97.

MOORE GC and BENBASAT I (1991) Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research* 2(3), 192–222.

MORIK K, IMBOFF M, BROCKHAUSEN P, JOACHIMS T and GATHER U (2000) Knowledge discovery and knowledge validation in intensive care. *Artificial Intelligence in Medicine.* 19(3), 225–249.

PRATT P and ADAMSKI J (1991) *Database systems: management and design*. Boyd & Frasier, Boston, MA.

RUCH P, COHEN G and OESTREICHER M (2002) Intelligent data analysis and clinical reports: applying bag-of-words approaches to corrupted collections. In: *IDAMAP 2002: Intelligent Data Analysis in Medicine and Pharmacology 2002* LUCAS P, ASKER L, and MIKSCH S, Eds, The European Conference on Artificial Intelligence, ECAI 2002. Lyon, France. July 23, 2002. http://www.cs.uu.nl/Blucas/idamap2002/idamap2002-proc.pdf (Retrieved 17 November 2003).

SHAHAR Y and MUSEN M (1996) Knowledge-based temporal abstraction in clinical domains. *Artificial Intelligence in Medicine* 8(3), 267–298.

TURBAN E and WATKINS PR (1986) Integrating expert systems and decision support systems. *MIS Quarterly* 19(2), 121–136.

WEEBER M and VOS R (1998) *Extracting Expert Knowledge from Medical Texts*. citeseer.nj.nec.com/19602.html (Retrieved 14 November 2003).